# Knowledge Spillovers Through FDI and Trade: The Moderating Role of Quality-Adjusted Human Capital

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**Abstract** The paper extends the findings of the Coe and Helpman (Eur Econ Rev 39(5):859–887, 1995) model of R&D spillovers by considering foreign direct investment (FDI) as a channel for knowledge spillovers in addition to imports. Deeper insights on the issue are provided by examining the inter-relationship between knowledge spillovers from imports and inward FDI. Furthermore, human capital is added to the discussion as one of the appropriability factors for knowledge spillovers, with special focus on its quality-content, using journal publications and patent applications. Applying cointegration estimation method on 20 European countries from 1995 to 2010, the direct effects of FDI-related as well as import-related spillovers on domestic productivity are confirmed. Furthermore, a strong complementary relationship is found between knowledge spillovers through the channels of imports and inward FDI. When considering quality-adjusted human capital, countries with better human capital are found to benefit not only from direct productivity effects, but also from absorption and transmission of international knowledge spillovers through imports and inward FDI. Finally, technological distance with the frontier does not appear to play a role in the absorption of import and FDI related knowledge spillovers.

## 1 Introduction

In the endogenous growth literature, the importance of international knowledge spillovers in explaining domestic productivity is widely acknowledged. Prior research on technological progress (Romer 1989; Aghion and Howitt 1992;

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A. Pyka, U. Cantner (eds.), *Foundations of Economic Change*, Economic Complexity and Evolution, DOI 10.1007/978-3-319-62009-1_16

Grossman and Helpman 1991; Coe and Helpman 1995; Engelbrecht 1997) proposes that a country's productivity depends not only on its own R&D efforts but also on foreign R&D, transmitted through channels of knowledge spillovers. In identifying the mechanism for knowledge spillovers, a considerable body of theoretical and empirical literature focuses on international trade as the most important channel through which knowledge and technology are transferred across boundaries. Other studies claim that international trade accounts for only 20% of productivity from foreign R&D and subsequently propose alternate spillover channels—such as outward and inward FDI (Wang and Blomström 1992; Borensztein et al. 1998; Glass and Saggi 1998; Xu and Wang 2000; Branstetter 2006), labor mobility and social networks (Bernard and Bradford Jensen 1999; Keller 2004), patent citations (Eaton and Kortum 1996, 1999; Xu and Chiang 2005) and cross-licensing (Lee 2006) to explain productivity growth.

While existing research addresses different channels through which external knowledge and foreign technologies are transferred across countries, this paper restricts its attention to knowledge spillovers via imports and inward FDI to ensure better identification of the spillover channels, as well as to provide for an easy comparability with standard literature on the topic (Grossman and Helpman 1991; Benhabib and Spiegel 1994; Coe et al. 1997; Coe and Helpman 1995). Trade in tangible intermediate inputs, manufactured goods and capital equipments result in efficient use of domestic resources and hence raises domestic productivity. Furthermore, it enables open communication among trade partners that leads to "cross-border" learning about foreign technologies and materials, production processes and organizational routines. Outward FDI enables greater returns on domestic investments by exploiting a foreign country's competitive advantage. Inward FDI, on the other hand, leads to greater access and diffusion of foreign technologies, productivity gains, forward and backward linkage effects and introduction of new skills and organizational practices in host countries. Furthermore, following from the literature on location choice and appropriability conditions relating to FDI (Feinberg and Majumdar 2001; Alcácer and Chung 2007), FDI enhances the ability of the country to absorb potential spillover-benefits related to investment.

Evidently, the literature on international trade and inward and outward FDI as spillover channels is extensive. However, what has been discussed so far are the respective effects of trade and of FDI on domestic productivity, assuming them to be two unrelated channels of spillovers. This constitutes an important drawback given the fact that trade and FDI are very much related (Brainard 1997) and therefore the complementarity or substitutability needs to be analyzed when examining their impact on productivity growth. Knowledge spillovers from trade can occur through the import of intermediate inputs and high-tech merchandise and services, while that from FDI can occur through channels of backward linkages (Javorcik 2004), vertical linkages in the form of spillovers to suppliers and customers (Lall 1980), worker mobility (Blomström and Kokko 1998) and demonstration effects in the form of imitation and reverse engineering (Saggi 2006). Yet, irrespective of the nature of spillovers through trade and FDI, empirical evidence remains inconclusive regarding their exact relationship (Fontagné 1999; De Mello and Fukasaku 2000).

The relationship between knowledge spillovers and productivity has also received much attention from labor economists in the last few decades. Education of the labor force and their accumulated stock of human capital significantly determine a country's ability to create new ideas and to adapt old ones (Lucas 1988; Nelson and Phelps 1966; Borensztein et al. 1998; Xu and Wang 2000). Apart from this direct effect on productivity growth, human capital also raises domestic productivity through greater absorption and diffusion of international technological spillovers and provision of suitable appropriability conditions for FDI. Existing literature in this regard suggests that an adequate level of human capital is necessary for technological spillovers to have a significant positive impact on domestic productivity. However, despite theoretical predictions, empirical findings on the exact relationship between channels of technological spillovers and the level of human capital in determining productivity growth remain inconclusive (Blomström et al. 2003). Various explanations for the inconsistent findings are provided in the literature, the most important being the way human capital stock is measured and compared across countries (Ramos et al. 2010).

Based on the above arguments, this study provides an integrated approach to better explain specific mechanisms by which spillover channels raise domestic productivity and the role of human capital therein. Specifically, it makes advances in the following directions: First, the Coe and Helpman (1995) model of R&D spillovers is extended by additionally analyzing FDI as an important channel for knowledge spillovers and the impact of trade and FDI-related knowledge spillovers on domestic productivity is investigated. However, unlike existing studies that explain trade and FDI as two independent channels of spillovers, the current study considers them as strongly overlapping and analyzes their relative and combined effect on productivity. Second, in this study human capital is considered not only as an ordinary input in the domestic production function, but also as a moderating variable that provides necessary conditions for absorption and transmission of trade and FDI-related knowledge spillovers and subsequent productivity growth. Accordingly, a quality-based index of human capital is proposed that allows for comprehensive and systematic comparison of human capital stocks across countries. Finally, this study builds on the catching-up hypothesis that countries farther away from the technological frontier benefit more from knowledge spillovers, and compares productivity effects of knowledge spillovers between countries with large distance to the technological frontier and countries with relatively smaller distance to the technological frontier.

The rest of the paper is organized as follows: Section 2 gives the conceptual background on knowledge spillovers through international trade and FDI and an overview of quality-based indicator of human capital. Section 3 introduces the econometric models and Sect. 4 discusses the data. Section 5 presents the econometric methodology considered to analyze the relevant research questions. Section 6 summarizes the main findings and Sect. 7 discusses the results.

# 2 Conceptual Background

## 2.1 Knowledge Spillovers Through International Trade and Foreign Direct Investment

Literature on the theory of endogenous technological progress presents mixed evidence on the importance and relative effectiveness of knowledge spillovers for the domestic economy. Earlier studies go back to Grossman and Helpman (1991), (henceforth GH) who formulate a theoretical model of product-variety where total factor productivity of a country increases with the number of varieties of intermediate products available in the market, and the share of labor employed in their production. Furthermore, the authors show that changes in the degree of openness of an economy, as measured by the level of trade promotion or trade protection, also affect the long-run growth rate, the transition to the steady state, the volume of bilateral trade and the level of social welfare. Extending GH, Coe and Helpman (1995) (henceforth CH) study the role of knowledge spillovers from foreign innovative activities through the channel of international trade. The authors argue that, in addition to domestic innovative efforts measured by profit maximizing R&D investments of entrepreneurs, foreign innovative activities also affect technological progress in the home country. Hence, total factor productivity is defined as a function of domestic R&D and foreign R&D. There can be direct and indirect benefits of foreign R&D to domestic economies. A direct impact arises from the direct transfer of technology while indirect benefits are realized through transmission channels such as trade and foreign direct investment. In the context of their paper, the extent to which these foreign R&D efforts can be transferred depends on how open the country is to international trade. Using the panel cointegration technique for long-run relationship on data for OECD countries for the period 1971–1990, the authors find that there is a close link between factor productivity and domestic as well as foreign R&D capital stocks. Moreover, trade is found to play an important role in transferring R&D related know-how from partners to home countries. Other empirical studies, such as Lichtenberg and Pottelsberghe de la Potterie (1998) and Kao et al. (1999) reach similar conclusions for different countries.

So far, most seminal papers analyzing the relationship between international knowledge spillovers and productivity have considered trade as the most important channel for knowledge spillover. Keller (1998), contrariwise, studies the robustness of CH results using Monte-Carlo-based test and challenges the findings that international R&D spillovers are trade related. In the Monte-Carlo experiment, international R&D spillovers are studied for randomly matched trade partners and comparison is then made between true values and ones generated by a simulation exercise. The findings suggest that the results of CH do not change even when the trade partners are randomly matched, which casts doubts on the claim that the pattern of international trade is important in knowledge spillovers. In response to Keller's critique, Coe and Hoffmaister (1999) show that a more sophisticated methodology for assigning random weights, as compared to Keller (1998), yields insignificant effects of spillovers on total factor productivity, a result that supports the earlier findings of Coe and Helpman (1995). Nevertheless, the results of Coe and Helpman (1995) appear to be sensitive to the choice of methodology and hints towards the need for the inclusion of trade unrelated channels of international technology diffusion. Consequently, a second strand of literature introduces FDI as an additional channel for international knowledge spillovers[1] and investigates the effect of FDI-related knowledge spillovers on domestic productivity. Hejazi and Safarian (1999) include FDI weighted R&D in the CH model in addition to import weighted R&D for G6 countries. Similar to the CH study, the authors find that both foreign and domestic R&D significantly affect domestic productivity. Additionally, the coefficient for FDI weighted foreign R&D is found to be higher than the trade weighted R&D variable, while the inclusion of FDI significantly reduces the significance of trade weighted foreign R&D. Moreover, they find that, when R&D variables are interacted with trade openness, they lose significance. The authors interpret this result suggesting that, irrespective of the extent to which the economy is open, technological spillovers do take place through FDI and trade. Branstetter (2006) studies the scope of technological spillovers through FDI by Japanese firms to US using patent citations from Japanese firms in the US patent office and argues that knowledge spillovers can go in either direction: firms investing in the host country bring knowledge from the home country and also learn from the domestic pool of knowledge in the home country. Results, robust to US-Japan technological alliances, suggest that FDI not only brings information into home country but also benefits the investing firm through the local stock of knowledge. Exploring further at the firm level, some studies examine the spillovers through backward and forward linkages. Javorcik (2004) uses panel data for Lithuanian firms and finds evidence only for backward linkages and not for forward linkages. Similarly, Kugler (2006) and Bwalya (2006) find evidence for backward linkages but not for forward linkages in Colombian and Zambian manufacturing sectors, respectively. Schoors and Tol (2002), however, in addition to evidence for spillovers through backward linkages, find negative spillovers effects through forward linkages.

In recent years, both international trade and FDI have been added as spillover channels in the productivity equation. Xu and Wang (2000), for example, examine the relationship between MNC activities (outward FDI) and trade in capital goods and technology diffusion for 21 OECD countries over the period 1971–1990 and find contrasting results. While a significant positive impact of foreign R&D spillovers through the channels of international trade and outward FDI is found on domestic total factor productivity, no such effect is found with respect to inward FDI. The authors interpret the results in terms of methodological limitations and the unavailability of quality data, while acknowledging the need to give greater

[1]Our definition of knowledge spillovers in this paper includes both voluntary knowledge transfers and involuntary knowledge spillovers.

attention to econometric issues. Keller (2010) proposes a theoretical framework in identifying the contribution of international trade and FDI in the economic performance of a country and finds that geographical proximity is an important condition for knowledge diffusion. Furthermore, the author claims that the two channels are indeed correlated and therefore empirical studies should focus on understanding this relationship. Saggi (2002), in a detailed review of the literature, suggests that growth enhancing effects of FDI are larger in countries that follow export promotion rather than import substitution strategies. This is because countries that follow more open trade regimes usually target the bigger global market as against countries that undertake import substitution, and therefore attract more FDI. Thus the trade policy regime is found to be an important determinant of the effect of FDI on the domestic economy, necessitating the need to examine how they interact when included together in the productivity model.

While theoretical predictions on the inter-relationship between international trade and FDI are significant, empirical evidence remains scarce. Filippaios and Kottaridi (2008) compare the investment development path between the EU and CEEC and find a strong complementarity between inward FDI and imports in determining international investors' behavior. Fontagné (1999), in a review of literature, states that, while studies in the 1980s claimed international trade to have generated FDI, in recent years the causality has been reversed. Based on these claims, one can expect that the relationship between trade and FDI varies with several micro and macro characteristics such as firm attributes and market orientation, sectoral affiliation or the country under analysis. From the perspective of the investing (home) country, outward FDI can be considered a substitute for exports because of increased production and the sale of finished goods by the foreign multinational corporations (MNC) established in the host market. However, inward FDI can increase the host country's imports by acquiring raw materials and intermediate inputs necessary for production by foreign multinational corporations to be imported from the parent country. The unavailability of appropriate intermediate products, quality considerations or highly-specific production process of the foreign affiliates in the host country can trigger such a complementary relationship. The literature on gravity models (Brenton et al. 1999) also provides similar arguments. In summary, although the direction of correlation (complementarity or substitutability) between trade in imports and inward FDI is a matter of debate, these two channels seem to be interlinked in encouraging productivity growth. However, no evidence exists with respect to the dynamics of knowledge spillovers from inward FDI and imports and how they interact with one another in promoting domestic productivity growth. The first and foremost contribution of the study reflects this consideration. The a-priori assumption here is that inward FDI encourages imports of technologically intensive intermediate goods and services from the parent country and transfers the capabilities to use technologically advanced products to workers hired from the domestic labor market. Therefore, we expect a complementary relationship between the two spillover channels. Based on this expectation, we examine their individual as well as combined impact as a spillover mechanism on domestic productivity growth and propose the following hypotheses:

**Hypothesis 1a:** Knowledge spillovers through imports positively affect domestic productivity.

**Hypothesis 1b:** Knowledge spillovers through inward FDI positively affect domestic productivity.

**Hypothesis 2:** The productivity-enhancing effects of knowledge spillovers through imports are reinforced by high degrees of FDI.

## *2.2 Moderating Knowledge Spillovers: Human Capital*

The relevance of trade and FDI as channels for knowledge transfer is crucial for productivity, to say the least. However, mere access to foreign R&D stock, technologies and know-how is not enough to drive a country on the path of long-term development. It is equally essential for the external knowledge to be sufficiently absorbed and diffused throughout the economy. Herein lies the role of human capital as a measure of absorptive capacity in moderating the relationship between productivity and knowledge spillovers, and forms the second most important contribution of the current study.

In their seminal paper on the two faces of R&D, Cohen and Levinthal (1989) argue that, while the existence of external knowledge linkages is beneficial, firms necessarily should have an adequate level of absorptive capacity in order to materialize beneficial spillovers from such external linkages. Accordingly, firms should invest in the development of such absorptive capacity by undertaking internal R&D activities. Discussing absorptive capacity within a human capital framework, Nelson and Phelps (1966) propose that, in a technologically progressive economy, the more educated the innovators, the quicker will be the speed of introduction of new techniques of production, and this will subsequently speed up the process of technological diffusion. Postulating two theoretical models of technological diffusion, the authors indicate that the payoff to increased educational attainment (that is, the rate of return to education) is greater the more technologically progressive the economy. Also, while the growth of technology frontier reflects the rate at which new discoveries are made, the growth of total factor productivity (TFP) depends on the implementation of these discoveries and varies positively with the distance between the technology frontier and the level of current productivity, which again depends on the level of human capital. Following similar arguments, Engelbrecht (1997) builds upon CH's model by including human capital as an additional variable accounting for non-R&D related innovation activities. Measuring human capital by interpolating Barro and Lee (1993) data on average years of education of the labor force above 25 years of age for 21 OECD countries, the author finds a direct effect of this variable on domestic productivity, technology catch-up and the absorption of foreign technology. Similar studies (Frantzen 2000; Griffith et al. 2002; Barrios et al. 2007; Kwark and Shyn 2006; Teixeira and Fortuna 2010) also confirm these findings.

Absorptive capacity measured in terms of human capital is also related to the literature on spillover channels where researchers have established the relationship between domestic human capital stock, international trade and FDI. Miller and Upadhyay (2000) suggest that the impact of human capital in a country is conditioned upon the degree to which the economy is open to international trade. Using data for a sample of developed as well as developing countries, the authors find that for low degrees of trade openness, the effect of human capital on total factor productivity is negative while for greater degrees of trade openness, the effect is positive and highly significant. While the relationship between trade and human capital is quite straightforward, the same cannot be said with respect to FDI. Borensztein et al. (1998) claim that the productivity effect of FDI will depend on the educational characteristics of the host or receiving countries. Examining the effect of FDI on economic growth in a cross-country analysis during 1970–1989 and measuring human capital as average years of schooling of male pupils (Barro and Lee 1993), the authors find direct as well indirect effects of FDI on productivity growth. Not only does greater FDI raise productivity, but the magnitude of the effect depends significantly on the domestic human capital stock of the country. Similarly, Blomström et al. (2003) suggest that, while FDI inflow leads to absorption and diffusion of foreign technology through the upgradation of local skills, a host country's level of human capital also determines the level of FDI it attracts. In other words, a greater level of human capital should attract more technologically intensive FDI and MNC operations as compared to weaker economies with lower level of human capital and absorptive capacity. Thus the extent and scope of knowledge spillovers from FDI depend on the readiness and absorptive capability of the domestic sector. This means that, while FDI reduces the cost of technology adoption, spillovers from FDI can also be negative because of the crowding out effect on domestic firms with insufficient absorptive capacity. Other studies that investigate the complex and non-linear relationship between channels of knowledge spillovers and human capital (Kokko et al. 1996; Kathuria 2002) suggest that FDI affects domestic productivity only in the presence of technological and market capabilities, a certain threshold level of human capital, and investment in learning and training.

It is evident from the studies mentioned above that the interrelationships between the channels of knowledge spillovers through FDI and trade and human capital have already been studied at various levels of aggregation. However, while theoretical predictions on the moderating role of human capital are substantial, empirical verification of the issue is mixed and rather inconclusive. The current study claims that the way human capital is measured in the existing literature might be one reason for the mixed evidence. So far, in previous studies, the human capital stock in a country is measured in terms of quantity-based indicators such as average years of schooling and graduation rates, and then related to knowledge spillovers and productivity growth. However, quantity-based indicators of human capital fail to account for quality differences in the education system and dimensions related to skills and competencies of human capital (OECD 2001). By this measure, an additional year of secondary education in a developed country, say the US, will be the same as in a less-developed country, say Bangladesh, even though US has a far superior education system in terms of quality. Furthermore, it neglects the differences in cognitive skills and problem-solving capabilities in students (Hanushek and Kimko 2000) and therefore renders the measure incomparable across countries. What is needed, therefore, is a systematic analysis of the role of human capital, taking into account the quality differences across countries that, in turn, affect the speed of absorption of knowledge spillovers through trade and FDI. To the best of our knowledge, no studies have so far provided a quality measure of human capital in analyzing the productivity effects of knowledge spillovers. Addressing this limitation, the paper uses secondary data for human capital based on average years of schooling and returns to education and adjusts it for quality using patents and publications. The following section explains the quantity-quality indicators and the choice of proxies for human capital measurement in more detail.

## *2.3 Quantity vs. Quality of Human Capital*

Traditionally, three approaches to human capital measurement have been pursued in the literature: cost-based approach, income-based approach and indicator-based approach. The cost-based approach (Kendrick 1976; Eisner 1988) measures human capital in terms of past investments undertaken by individuals, households, employers or government, and more recently in terms of the value of time devoted to the education of students. The income-based approach (Weisbrod 1961; Graham and Webb 1979; Jorgenson and Fraumeni 1989) measures human capital as the expected future earnings generated from human capital investments over the lifetime of a person. Finally, the indicator-based approach uses various measures as proxy for the stock of human capitalfor example, school enrollment rates (Barro 1991; Mankiw et al. 1992; Levine and Renelt 1992), educational attainment of adults aged 25 years and above (Barro and Lee 1993), average years of schooling (Benhabib and Spiegel 1994; Barro and Sala-i-Martin 2004; O'Neill 1995; Barro 1997; Krueger and Lindahl 2001), student-teacher ratio (Wang and Wong 2011), graduation rates, dropout rates and adult literacy rates (Azariadis and Drazen 1990; Nehru et al. 1995; Barro and Lee 1996). However, these measures fail to account for differences in the education systems across countries and attach equal weights, irrespective of quality differences and mismatch in the cognitive skills of students. Because quality of human capital, and not mere quantity, is an important indicator of economic growth, the current study provides a new measure of the human capital stock adjusted by its quality and subsequently examines its effect in moderating the relationship between knowledge spillovers and productivity.

One approach that has gained much attention in recent years as a quality-based measure of human capital is international test scores that capture the cognitive performance of students globally (Hanushek and Kimko 2000). For example, the Trends in International Mathematics and Science Study (TIMSS) is a worldwide study program provided by the International Association for the Evaluation of

Educational Achievement (IEA) that assesses mathematics and science knowledge in fourth and eighth grade students. The study, first conducted in 1995 and thereafter conducted every four years globally, provides additional information on the learning conditions in countries and hence accounts also for the diversity in the education systems worldwide. A similar assessment program provided by the OECD is the Programme for International Student Assessment (PISA) that tests cognitive skills like reading, mathematics, science and problem solving of 15–16 year olds. This program, started in 2000 and repeated every three years, aims at measuring "education's application to real-life problems and lifelong learning" (OECD 2001). Another recent international study provided by the OECD is the Programme for the International Assessment of Adult Competencies (PIAAC) that tests skills and competencies of adults (aged 16–65) in terms of literacy, numeracy and problem-solving in technology-rich environments. PIAAC, first conducted in 2011–2012 in the US, therefore allows for systematic comparison across countries by focusing on the cognitive and workplace skills, educational background and occupational attainment of adults around the world. Other similar examples of standardized tests are the Graduate Record Examination (GRE), the Graduate Management Admission Test (GMAT) and the Scholastic Aptitude Test (SAT). Although most of these standardized tests provide time series across educational assessments for countries, the availability of annual data for a longer time frame and for all sample countries considered in the current analysis is a major issue. The International Mathematical Olympiad (IMO) serves as an alternative, by providing yearly scores in mathematics for pre-collegiate students worldwide. The IMO, first held in 1959 in Romania, is a 42-point mathematical Olympiad that ranks countries based on the cumulative test scores. It is not a proxy for basic skills in the population, rather a proxy for the beyond-the-classroom education a country provides to exceptionally high-skilled students in mathematics and science. IMO test scores are available for long time periods and for all our sample countries, with the only limitation arising from the structure of the test and sample-size.[2]

A second alternative in this regard is journal publications. An academic journal is a peer-reviewed periodical that constitutes publication of original research, review articles and book reviews in all fields of academia. It is frequently used as a proxy for the scientific environment, and the research activities undertaken in a country. Typically, the quality of an academic journal is measured by its 'impact factor', that is, the average number of citations received from later publications, and journals with higher impact factors are considered to be of higher quality than those with lower ones. Therefore, one can assume that higher the number of journal publications in a country, the richer is its knowledge base and human capital. Furthermore, data on publication is readily available for all countries in the sample for a long time frame.

[2]Please see Table 4 in the Appendix for an overview on pros and cons of using the different proxies for quality adjustment of human capital.

A third alternative is patents. Patents are generally used as a proxy for innovativeness in regional- and firm-level analysis. Although patents are a direct measure of innovative activity, they still suffer from some potential problems. Despite being very narrow in scope, patents can be used as a proxy for the quality of education. Countries with a better quality of education are more likely to innovate than countries with poorer quality. Therefore, the relatively higher number of patents in a given year can hint towards the better education system.

Subsequently, the current analysis uses data from the World Bank for journal publications in science and technology (S&T, having non-zero impact factors), and patent applications as weighting parameters for the Barro and Lee (2010) quantity-based measure of human capital. While the details of the construction can be found in the data section, Fig. 1 shows how the respective positions of the countries change when we adjust the conventional measure of human capital with quality. We rank 20 countries in our sample based on both adjusted and unadjusted human capital indices and subtract their respective ranks for 1995 and 2010. The figure shows the plots of differences in relative ranks of 20 European countries in the sample. The positive differences are the gains in ranks after adjustment for quality, which already points to the fact that the conventional human capital index underestimates the human capital of these countries and vice versa. Most significant differences are observed for Czech Republic for which the rank drops from 1st to 13th in 1995 and 1st to 15th in 2010. Similarly, Estonia goes down in the ranks from 8th to 18th in 1995 and 3rd to 19th in 2010. However, the rank for the United Kingdom increases from 18th to 4th in 1995 and 20th to 4th in 2010, which is similar to the rank of the United Kingdom according to TIMSS 2011.

Based on these differences, the second contribution of the study is the analysis of the moderating role of quality-adjusted human capital in the knowledge

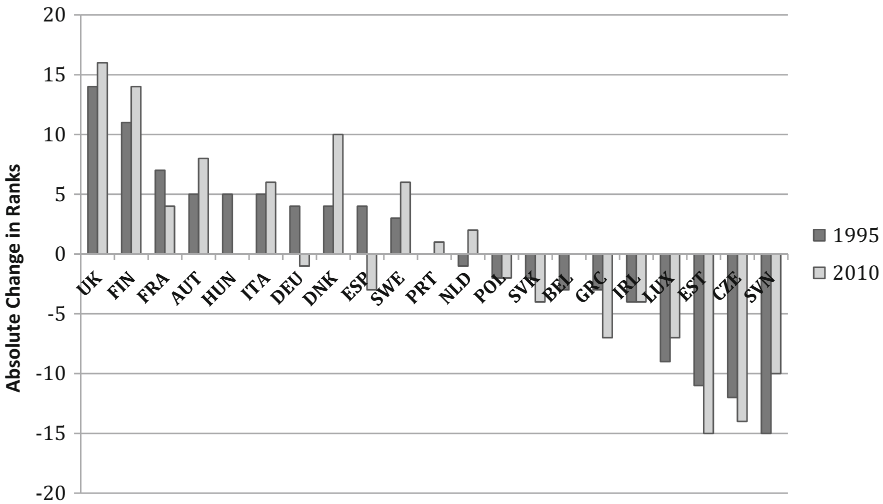


**Fig. 1** Change in ranks after quality adjustment of human capital

spillover-productivity link. If imports, for example, are technology intensive and the importing country does not have adequate human capital to learn from the knowledge embedded in the imports, then spillovers will not adequately affect overall productivity of the economy. Proposing similar arguments with respect to FDI, it can therefore be argued that countries with better human capital benefit more from knowledge spillovers through channels of trade and FDI. We assess the moderation of human capital using interactions between knowledge spillovers and quality-adjusted human capital, while acknowledging the direct effect of human capital on domestic productivity. Accordingly, the following two hypotheses are proposed:

**Hypothesis 3a:** Human capital positively affects domestic productivity.

**Hypothesis 3b:** Human capital positively moderates the relationship between knowledge spillovers and domestic productivity.

Finally, in a cross-country analysis it is important to assess the heterogeneous country specific characteristics. Countries at different growth trajectories than others might benefit differently from the knowledge spillovers relative to their level of productivity. According to the catching-up hypothesis, countries with productivity levels significantly lower than the frontier are expected to gain more from international knowledge spillovers than countries closer to the frontier (Griffith et al. 2002; Castellani and Zanfei 2003). This is because technologically-backward countries benefit from imitation of technologies introduced in leader countries, and usually the cost of imitation is lower than that of innovation closer to the frontier (Barro and Sala-i-Martin 2004). Therefore, the wider the technology gap between the lagging country and the leader, the higher the scope of technology adoption and international knowledge spillovers and subsequently higher the gains in productivity. We capture this effect by introducing a technological gap variable in the main regressions and also interact with the spillovers variables to assess whether countries far away from the technological frontier gain more from knowledge spillovers.

**Hypothesis 4:** Countries significantly distant from the technological frontier gain more from international knowledge spillovers.

# 3 Models

## *3.1 Model 1: CH Specification*

The main model to test our hypotheses 1a and 1b builds upon the CH specification (corresponding to Eq. (2) in the CH) and is formulated as follows:

$$logTFP_{i,t} = \beta_o + \beta_1 logR\&D_{i,t} + \beta_2 ImportSpill_{i,t} + \varepsilon_{i,t} \tag{1}$$

where *TFP* is total factor productivity of country *i*, R&D is per capita R&D stock in importing country (country *i*), $ImportSpill_{i,t} = \Omega \mathrm{logR\&D_{i,t}}$ represent per capita import-related spillovers where $R\&D_{i,t}$ is stock of R&D in the exporting country (country $j$) and $\Omega$ is the ratio of imports from country $j$ to GDP in country $i$.

## 3.2 Model 2: Base Specification (Extension of Model 1)

We extend the CH model in Eq. (1) by including quality-adjusted human capital and FDI as an additional source of international knowledge spillovers in Eq. (2).

$$\begin{aligned} logTFP_{i,t} = \beta_o + \beta_1 logR\&D_{i,t} + \beta ImportSpill_{i,t} + \beta_3 logFDI_{i,t} \\ + \beta_4 logHCQ_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $HCQ$ is the quality is adjusted human capital variable and $FDI$ is per capita stock of inward FDI in country $i$. This, therefore, captures the direct impact of human capital on a country's productivity.

## 3.3 Model 3: Complementarity Between Import-Related Spillovers and FDI

Model 3 aims to capture the complementarity between import-related spillovers and FDI as outlined in hypothesis 2. The interaction between import-related spillovers and FDI is used to determine whether import-related spillovers and FDI are complements or substitutes.

$$\begin{aligned} logTFP_{i,t} = \beta_o + \beta_1 logR\&D_{i,t} + \beta_2 ImportSpill_{i,t} + \beta_3 logFDI_{i,t} + \beta_4 logHCQ_{i,t} \\ + \beta_5 \left(ImportSpill_{i,t} * FDI_{i,t}\right) + \varepsilon_{i,t} \end{aligned} \tag{3}$$

## 3.4 Model 4: Human Capital as a Moderator of Knowledge Spillovers

Interactions of import-related spillovers and FDI with quality-adjusted human capital are introduced in Model 4. Here we aim to test our hypothesis 3 where we expect human capital to moderate the relationship between knowledge spillovers and TFP.

$$\begin{aligned} logTFP_{i,t} = \beta_o + \beta_1 logR\&D_{i,t} + \beta_2 ImportSpill_{i,t} + \beta_3 FDI_{i,t} + \beta_4 HCQ_{i,t} \\ + \beta_5 \left(ImportSpill_{i,t} * HCQ_{i,t}\right) + \beta_6 \left(FDI_{i,t} * HCQ_{i,t}\right) + \varepsilon_{i,t} \end{aligned} \tag{4}$$

### 3.5 Model 5: Role of Technological Gap

Finally, in Model 5, to test our hypothesis 4, we include the technological gap between country $i$ and the technological frontier in model 2 (Eq. 5a below).

$$logTFP_{i,t} = \beta_o + \beta_1 logR\&D_{i,t} + \beta_2 ImportSpill_{i,t} + \beta_3 logFDI_{i,t} + \beta_4 logHCQ_{i,t} + \beta_5 logGap_{i,t} + \varepsilon_{i,t} \quad (5a)$$

where *Gap* is the distance between country with highest TFP in the sample minus TFP of country $i$. In subsequent models, we include interactions of technological gap variable with import-related spillovers and FDI to test whether technologically distant countries benefit more from international knowledge spillovers (models 5b and 5c).

$$logTFP_{i,t} = \beta_o + \beta_1 logR\&D_{i,t} + \beta_2 ImportSpill_{i,t} + \beta_3 logFDI_{i,t} + \beta_4 logHCQ_{i,t} + \beta_5 logGap_{i,t} + \beta_6 \left(ImportSpill_{i,t} * Gap_{i,t}\right) + \varepsilon_{i,t} \quad (5b)$$

$$logTFP_{i,t} = \beta_o + \beta_1 logR\&D_{i,t} + \beta_2 ImportSpill_{i,t} + \beta_3 logFDI_{i,t} + \beta_4 logHCQ_{i,t} + \beta_5 logGap_{i,t} + \beta_6 \left(FDI_{i,t} * Gap_{i,t}\right) + \varepsilon_{i,t} \quad (5c)$$

## 4 Data

The data sample covers the period from 1995 to 2010 and includes 20 European countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Portugal, Spain, Slovak Republic, Slovenia, Sweden and the United Kingdom. In what follows, we explain the construction and sources of the variables used in our empirical analysis.

### 4.1 Total Factor Productivity (TFP)

Total factor productivity is taken from Penn World Tables v8.0 and the following methodology has been used to calculate TFP:

$$TFP_{i,t} = \frac{Y_t}{Y_{t-1}} / Q_{t,t-1}$$

where

$$Q_{t,t-1} = \frac{1}{2}(\alpha_t + \alpha_{t-1})ln\frac{K_t}{K_{t-1}} + \left[1 - \frac{1}{2}(\alpha_t + \alpha_{t-1})\right]ln\frac{L_t}{L_{t-1}}$$

$Y$ is real GDP, $K$ is capital stock, $L$ is labor force engaged and $\alpha$ is output elasticity of capital (share of gross fixed capital formation in real GDP). Details of the calculation can be found in Inklaar and Timmer (2013).

## 4.2 R&D Capital Stock

Since data for R&D capital stock are not available for long time series, we calculate R&D capital stock using the perpetual inventory method for each country. Data for R&D flows are taken from OECD Database: "Main Science and Technology Indicators" to estimate stock values, and subsequently R&D capital stock for the first year is calculated using following formula:

$$R\&D_{i,t=1} = \frac{R\&D_{i,t=1}^{flow}}{g + \delta} \tag{6}$$

where $R\&D_{i,t=1}^{flow}$ is R&D expenditure flow for the first year, $g$ is the compound annual growth rate of R&D expenditure flows and $\delta$ is the depreciation rate of investment assumed at 15%.

Although our sample for estimations starts from 1995, for calculation of R&D capital stock, we use data from 1981 to minimize the potential bias in the construction of the first year's capital stock. For some countries such as the Czech Republic and Estonia, available data series start from 1991 and 1998, respectively. In such cases, initial capital stock is calculated for available years and linearly extrapolated wherever necessary. Similarly, linear interpolation is used to fill-in missing values of R&D expenditure flows. Capital stock for later years is calculated by adding the flow of R&D expenditure to the previous year's capital stock after adjusting it for depreciation. Formally:

$$R\&D_{i,t} = R\&D_{i,t-1}{}^*(1 - \delta) + R\&D_{i,t}^{flow}$$

## 4.3 Human Capital Variables

The unadjusted human capital index is taken from Penn World Tables v8.0. This index is based on averages years of schooling from Barro and Lee (2010) and assumed rate of return corresponding to Psacharopoulos (1994). The human capital variable based on the above mentioned criteria provides meaningful information about the quantity of human capital for the population above 15 years of age. However, it does not account for the quality of education. This caveat of the index limits its usefulness in cross country analysis, following which we weight human capital variable with proxies of quality of education. The variables used as proxies for the quality of education (as explained in Sect. 2.3) are (a) aggregated journal articles in science and technology (World Development Indicators (WDI) and (b) aggregated patents (WDI). The benefit of using aggregated patents and publications from WDI compared to the Web of Science Database is that OECD data are weighted for co-authorship. If there is more than one author for a publication or a patent, OECD distributes the share to all coauthors to avoid double counting. The quality adjusted human capital (HCQ) variable is calculated using Eq. (7).

$$HCQ_{i,t} = HC_{i,t}{}^{*}\left(\frac{Publications_{i,t}}{L_{i,t}} + \frac{Patents_{i,t}}{L_{i,t}}\right) \tag{7}$$

where $HC$ is the human capital index based on average years of schooling and returns to education, Publications represents the journal publications in science and technology from the World Bank, Patents is number of patent applications per country in all fields and $L$ is the engaged labor force.

## 4.4 Knowledge Spillovers

In the context of this study, knowledge from one country to another is transferred through the channel of imports and FDI. Countries spend on R&D to develop new knowledge. The pieces of new knowledge from R&D activities over the years jointly represent the knowledge stock of the country. Therefore, we use R&D capital stock as a proxy for the knowledge stock. Some component of the overall knowledge stock is embodied in every product a country produces. Therefore, by exporting its products to other countries, a country also shares some of its knowledge with the importing country. In order to simplify the presentation, the subscript for time is suppressed in Eq. (8). Formally:

$$ImportSpill_i = \sum_{j=1}^{n-1} \frac{Imports_{i,j}}{Y_i} logR\&D_j \tag{8}$$

where *Imports* represent imports of country $i$ from country $j$. $Y$ is the real GDP of country $i$ and $logR\&D_j$ is R&D capital stock of country $j$.

We use bilateral imports data to calculate import-related spillovers for each country in each year. Spillovers are then aggregated across partners to calculate the overall spillover index for each country $i$. Assuming that knowledge embodied in technologically intensive products is larger than primary commodities, we expect spillovers to be greater for industries with a high level of technology and restrict our analysis to high-technology and medium-high-technology imports, according to the OECD intensity classifications.[3]

Calculation for knowledge spillovers through FDI ideally should also follow a similar strategy, as explained above. However, in the absence of quality data in bilateral FDI flows, such calculation is not possible. Therefore, we use the stock of inward FDI to approximate the knowledge flows through FDI.

## 4.5 Technological Gap

Growth theory suggests that countries that are technologically distant from the frontier tend to catch-up faster than the technologically proximate countries. In order to capture this effect, we use the technological gap (Gap) variable as shown in Eq. (9). The Gap variable for each country i in each year t is the difference between the TFP of the TFP leader and the TFP of country i for each time period t.

$$Gap_{i,t} = \frac{TFP_{leader,t} - TFP_{i,t}}{TFP_{leader,t}} \tag{9}$$

where $TFP_{leader,t}$ is the TFP of technological leader at time $t$ and $TFP_{i,t}$ is the TFP of country $i$ at time $t$ (2005 = 1).

Table 1 provides an overview of descriptive statistics and Table 6 in the appendix provides the correlation matrix of variables used in the analysis. As shown by the number of observations, our dataset has a balanced panel structure. Apart from import spillovers, all variables are used in their natural logarithms. The *Gap* variable can take the value of 0 when the gap is calculated for the leading country. In such a case, the natural logarithm of a variable is undefined. Keeping this in view, we added 1 to Eq. (9) before applying natural logarithm. The correlation matrix in Table 6 shows that correlation coefficients are less than 0.5 for most of the variables. Two exceptions are correlation coefficients between $log(HCQ)$ and

**Table 1** Descriptive statistics

| | log(TFP) | log(R&D) | ImportSpill | log(HCQ) | log(FDI) | log(Gap) |
|---|---|---|---|---|---|---|
| Mean | −0.031 | −5.843 | 0.034 | 11.874 | 8.702 | 0.394 |
| Median | −0.016 | −5.882 | 0.018 | 11.886 | 8.746 | 0.438 |
| Maximum | 0.141 | −1.712 | 0.274 | 14.677 | 11.397 | 0.650 |
| Minimum | −0.406 | −9.767 | 0.000 | 7.700 | 5.317 | 0 |
| Std. Dev. | 0.077 | 1.684 | 0.049 | 1.483 | 1.165 | 0.176 |
| Observations | 320 | 320 | 320 | 320 | 320 | 320 |

[3]ISIC Rev.2 Technology Intensity (See Table 5 in the Appendix).

*ImportSpill* and *log*(*HCQ*) and *log*(*Gap*). The presence of high correlation among explanatory variables could lead to a multicollinearity problem. Therefore, we relied on the mean variance inflation factor (VIF) for each estimated regression. Since all of the mean VIF scores are below 10, we conclude that multicollinearity is not present in our estimations.

## 5 Empirical Methodology

The data used in the current study are a panel of 20 European countries from 1995 to 2010. The natural candidates for estimation method in the case of panel data are fixed or random effects models, which are designed to account for country specific effects. However, there are at least two potential econometric problems that these methods do not take into account. First, the relationship between TFP and knowledge spillovers may not be unidirectional. Possible reverse causality in this case can result in endogeneity, where a crucial assumption of classical linear regression model $cov[X,c] = 0$ is violated and resulting estimates are biased. Second, variables used in our models have strong deterministic trend (Figs. 3, 4, 5, 6 and 7 in Appendix), the presence of which can result in spurious correlation. To avoid this problem, previous studies use variables in differences. However, by taking differences, important information embodied in the variables is lost (Coe and Helpman 1995).

In order to account for country specific effects and endogeneity in the absence of an ideal set of instruments at hand, generalized method of moments (GMM) provides a useful alternative. GMM uses lag structure of endogenous and predetermined variables to account for endogeneity and allows for dynamic modeling using lagged dependent variable. However, since GMM is designed for small T and large N, where N should be significantly larger than T, our $N = 20$ may not be large enough to satisfy this condition. Moreover, GMM is not designed to account for a long-run relationship in the presence of cointegration. Dynamic OLS provides a solution to the problems mentioned above, that is, it accounts for country specific effects, endogeneity, as well as the long run cointegrating relationship. Estimation using cointegration approach produces unbiased estimates without losing important information contained in data at levels. This procedure requires all variables to be $I1$ (integrated of order 1). Moreover, the variables are said to be cointegrated when the residual of the equations of interest are stationary. In other words, cointegration techniques for estimation can only be applied when all variables are stationary at first difference and their linear combination (residual) is stationary. In panel settings, a number of tests can be applied to test for unit-root as well as for cointegration. The most commonly used cointegration tests in panel data context are Pedroni (1999, 2004) and Kao (1999) tests. These tests use similar approaches but are based on slightly different assumptions. A brief overview of cointegration concept as well as tests for cointegration is presented in Appendix. There are two classes of panel unit root tests; one assumes a common unit root process for all cross sections (e.g. Levin et al. 2002; Breitung 2000) and the second one allows for individual unit-root processes (e.g. Im et al. (2003) (IPS), Fisher-type Dickey and Fuller (1979) (ADF) and Phillips and Perron (1988) (PP)). The assumption of a common unit root process across cross-sections can be too restrictive (Barreira and Rodrigues 2005). Therefore, we rely on IPS, ADF and PP tests for a unit root. Null hypothesis for these tests is the presence of a unit root.

## 6 Estimation Results

Estimation using panel cointegration methods, as explained in the previous section, requires all variables to be integrated of order 1 (non-stationary at levels but stationary at first difference) as well as their linear combination to be integrated of order zero (that is, the resulting residuals should be stationary at levels). The results of Pedroni and Kao tests for panel cointegration are presented under each model. Unlike the Kao test, the Pedroni test provides 11 test statistics under assumptions of joint unit root and individual unit root processes across cross sections. There is, however, no clear guideline on the decision rule to reach a conclusion on the existence of a cointegrating relationship. Moreover, the assumption of a common autoregressive process could be too restrictive (Barreira and Rodrigues 2005). Given these limitations, we rely, in addition to 11 test statistics of Pedroni, on the Kao test for cointegration. In most cases, 7 out of 12 tests show that the variables are cointegrated.[4]

The results of unitroot tests are provided in Table 2. The null hypothesis for the tests is the existence of a unit root. Test statistics show that all variables are non-stationary at levels and stationary at first difference (that is, they are $I(1)$) which is one of the necessary conditions for the use of the cointegration estimation method that we use further on.

Estimation results[5] for models (1)–(5c) are summarized in Table 3. Model 1, corresponding to Eq. (1) in the theory section, confirms the findings of CH. An increase in domestic R&D capital stock significantly increases TFP in the European countries considered. Additionally, and in line with hypothesis (1a), import related knowledge spillovers also have a positive relationship with TFP. The results show that, in addition to domestic R&D efforts (confirming the findings of CH), knowledge spillovers through imports in high and medium tech sectors are important for TFP in importing countries. This result shows support for hypothesis 1a. The result of the Kao cointegration test shows that the null hypothesis of no cointegration can be rejected at 1% level of significance. The Pedroni test for cointegration shows that

[4]Detailed results of cointegration tests are provided in Table 8 in the Appendix.

[5]Since our sample period includes the financial crisis in 2008–2009, an additional set of estimations was performed with a dummy for financial crisis (year 2008 and 2009). Even though the dummy was highly significant and negative, our findings were robust to its inclusion. Results are available from the authors on request.

**Table 2** Unitroot tests[a]

| Variables | IPS test (W-stat) | ADF test (Chi-square) | PP Test (Chi-square) |
|---|---|---|---|
| log(TFP) | 0.96 | 37.25 | 30.82 |
| Δlog(TFP) | −3.36*** | 76.68*** | 107.1*** |
| log(R&D) | 1.19 | 42.8 | 22.18 |
| Δlog(R&D) | −3.76*** | 78.3*** | 153.25 |
| ImportSpill | −1.44 | 18.94 | 17.09* |
| ΔImportSpill | −4.94*** | 95.04*** | 161.83*** |
| log(HCQ) | 3.67 | 24.15 | 44.57 |
| Δlog(HCQ) | −3.23*** | 72.16*** | 180.59*** |
| log(FDI) | 3.24 | 17.68 | 16.34 |
| Δlog(FDI) | −4.34*** | 88.63*** | 181.72*** |
| log(Gap) | 1.29 | 41.82 | 42.31 |
| Δlog(Gap) | −2.41 | 68.68*** | 142.7*** |

Null Hypothesis: Variables contain unitroot
[a]*IPS* Im-Persaran-Shin, *ADF* Augmented-Dickey-Fuller, *PP* Philip-Perron

5 out of 11 cointegration tests reject the null hypothesis of no cointegration, at least at 5% level of significance. In summary, 6 out of 12 cointegration tests confirm the presence of cointegration.

In model 2, we extend the CH model by including FDI stock (hypothesis 1b) and quality adjusted human capital (already for hypothesis 4). For model 2, 7 out of 12 cointegration tests confirm the presence of cointegration in the model. An increase in the stock of human capital is expected to improve TFP, as labor with better human capital is expected to be more productive. Similarly, the FDI stock is expected to improve TFP if knowledge embodied in the multinationals is reflected in the TFP of domestic firms. Our results show support for hypotheses 1b and 3a, that is, an increase in the FDI stock and quality adjusted human capital increases TFP in host countries. Hence, the additional consideration of these two variables improves the findings of CH by showing that human capital and the FDI stock also significantly explain the variation in TFP and therefore should be included in the model.

Model 3 tests for the complementarity between import-related spillovers and FDI (hypothesis 2). Results of cointegration tests for model 3 show that 7 out of 12 tests confirm the presence of cointegration. Studies on the complementary relationship between imports and FDI provide mixed evidence on technologically intensive multinationals importing hi-tech merchandise and intermediate inputs from their home countries in the absence of suitable production facilities in the host country, on the one hand, and increased inward FDI substituting imports of finished goods and services, on the other hand. The current study contributes to an understanding of this specific relationship, with the a-priori expectation that, in the context of knowledge spillovers by importing hi-tech manufacturing goods, FDI not only brings potential sources of external knowledge but also diffuses the know-how to use hi-tech manufacturing goods. Following this line of argument, we expect import related spillovers and FDI to complement each other and we test for the complementarity using interaction between import-related spillovers and

**Table 3** Estimation results

| | Model(1) | Model(2) | Model(3) | Model(4) | Model(5a) | Model(5b) | Model(5c) |
|---|---|---|---|---|---|---|---|
| log(R&D) | 0.267*** | 0.187*** | 0.262*** | 0.131*** | 0.206*** | 0.255*** | 0.218*** |
| | (0.034) | (0.027) | (0.023) | (0.026) | (0.025) | (0.027) | (0.025) |
| ImportSpill | 0.136*** | 0.738*** | −0.422*** | −0.909*** | 0.658*** | 0.759*** | 0.427 |
| | (0.037) | (0.204) | (0.059) | (0.096) | (0.158) | (0.157) | (0.423) |
| log(HCQ) | | 0.380*** | 0.255*** | 1.090** | 0.403*** | 0.381*** | 0.457*** |
| | | (0.042) | (0.033) | (0.043) | (0.042) | (0.046) | 0.040 |
| log(FDI) | | 0.056*** | 0.320*** | −0.054 | 0.06*** | 0.054*** | 0.063*** |
| | | (0.004) | (0.004) | (0.041) | (0.005) | (0.005) | (0.004) |
| log(FDI) × log(HCQ) | | | | 0.009*** | | | |
| | | | | (0.003) | | | |
| ImportSpill × log(HCQ) | | | | 1.120*** | | | |
| | | | | (0.011) | | | |
| log(FDI) × ImportSpill | | | 0.560*** | | 0.033* | −0.001 | 0.037** |
| | | | (0.007) | | | | |
| logGap | | | | | 0.033* | −0.001 | 0.037** |
| | | | | | (0.014) | (0.086) | (0.013) |
| log(FDI) × logGap | | | | | | 0.007 | |
| | | | | | | (0.009) | |
| ImportSpill × logGap | | | | | | | 0.181 |
| | | | | | | | (0.616) |
| $R^2$ | 0.898 | 0.965 | 0.977 | 0.974 | 0.973 | 0.978 | 0.978 |
| Adjusted $R^2$ | 0.874 | 0.978 | 0.971 | 0.969 | 0.967 | 0.973 | 0.974 |
| No of observations | 300 | 300 | 300 | 300 | 300 | 300 | 300 |
| Mean VIF | 1.12 | 1.82 | 5.04 | 1.73 | 1.94 | 2.87 | 1.97 |
| Pedroni | 5 out of 11 | 6 out of 11 | 6 out of 11 | 6 out of 11 | 6 out of 11 | 5 out of 11 | 5 out of 11 |
| Kao cointegration test | −1.94** | −2.43** | −3.66*** | −4.24*** | −2.91*** | −2.75*** | −3.46*** |

Dependent variable is log(TFP)
Null hypothesis for cointegration test is "no cointegration"
Pedroni test results presented above are number of significant test results out of 11
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

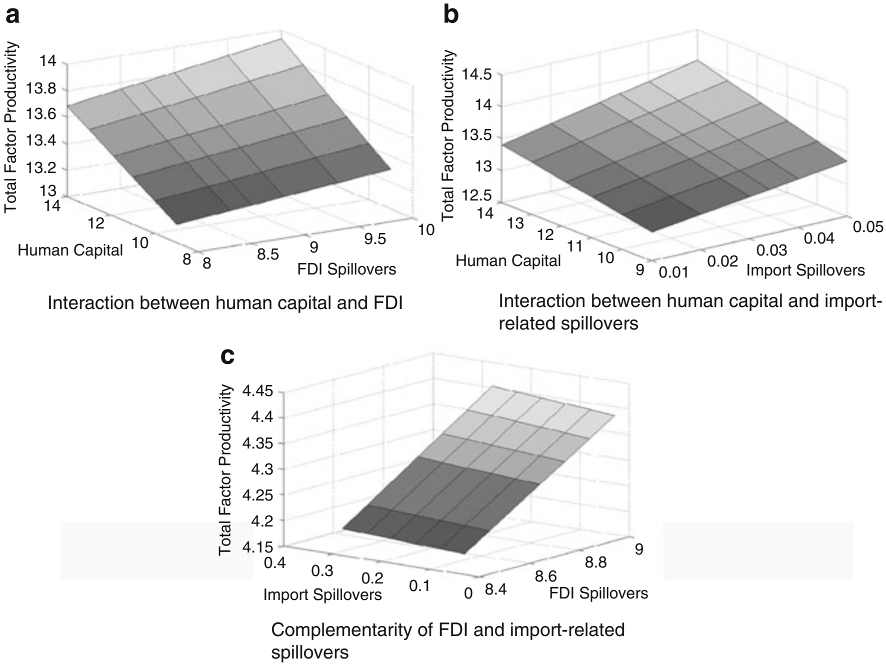


**Fig. 2** Graphical representation of the interaction effects

FDI in the main model. The positive and significant coefficient of interactions shows support for the complementarity hypothesis. In other words, results show that not only do import related spillovers and FDI affect TFP but also their joint effect raise domestic productivity. These findings show support for hypothesis 2 and form the first major contribution of the study. Graphical representation of this effect is shown in Fig. 2c which shows that the effect of import-related spillovers is strengthened when FDI spillovers are high. The switch of sign from positive to negative for import-related spillovers deserves an explanation. Since interpretation of the main effects has to be done jointly with the interaction term, the joint effect should be positive. Since the resulting magnitude of the overall effect is positive (0.560–0.422) even at the minimum level of FDI (5.317), the minimal overall effect of import-related spillovers is always positive.

In model 4 we test our hypothesis 3b where we include interactions of human capital with the FDI stock and import related knowledge spillovers. Similar to models 2 and 3, 7 out of 12 cointegration tests for model 4 confirm the presence of cointegration. The purpose of this model is to test whether human capital moderates the relationship between knowledge spillovers and TFP. Countries with better human capital are expected to gain more from knowledge spillovers through external sources, as it is easier for them to absorb the inflow of knowledge. Positive and significant coefficients of interaction terms, both with import related knowledge spillovers and with FDI stock, show support for hypothesis 3b. In other words, results suggest that countries with better quality of human capital benefit not only from direct effects of productivity, but also from productivity effects from international knowledge spillovers. Graphical representations of the moderating effect of human capital for import-related and FDI-related spillovers are shown in Fig. 2b and a, respectively. The negative coefficient for the import-related spillover variable has to be interpreted the same way as in model (3) (with the minimal log(FDI) value of 7.7). To check the appropriateness of our quality-adjusted human capital variable, in Table 7 in the appendix we present the estimation results with a traditional human capital variable as a moderator. Insignificant interactions in model 2(a) of Table 7 show that the quality of education matters for the absorption of technological knowledge, and from an empirical point of view it reaffirms the necessity of using quality-adjusted human capital measures in cross-country analysis.

Finally, three models (5a, 5b and 5c) test our final hypothesis (hypothesis 4) concerning the technological distance from the frontier. For model 5a, 6 out of 12 tests, while for models 5b and 5c, 7 out of 12 tests, confirm the presence of cointegration. We hypothesize that the relationship between international knowledge spillovers and TFP is stronger for technologically-lagging countries. Technological distance (Gap) determines the potential to improve, implying that countries too distant from the frontier may not learn too much due to the lack of absorptive capacity while countries too close to the frontier may not have much to learn from the exporting (investing) partner. The existence of such a non-linear relationship can be tested using a quadratic version of the technological gap in the model. We, however, could not find support for the quadratic relationship. The linear version of the technological gap variable was introduced in model 5a. A positive and significant coefficient shows that technologically distant countries catch up faster than the ones closer to the frontier. In models 5b and 5c, we introduce interactions of the technological gap with FDI and import related spillovers. Using similar line of argument, we expect technologically distant countries to have a stronger relationship between international knowledge spillovers and TFP, as they have more to learn than countries technologically proximate to the frontier. The results do not show support for hypothesis 4. Both interactions, FDI with a gap variable and import related spillovers and gap, do not appear to have a significant relationship with TFP. In other words, the result shows that the relationship between international knowledge spillovers and TFP does not vary with the change in technological distance from the frontier.

## 7 Conclusion

The endogenous growth literature suggests that, while own R&D efforts as well as foreign R&D transmitted through channels of knowledge spillovers are necessary for explaining domestic productivity growth, it is not a sufficient condition. In order to understand the underlying mechanism through which international knowledge spillovers affect domestic productivity, it is essential to accommodate human capital in the analysis. However, the existing literature on the relationship between human capital and channels of knowledge spillovers provides mixed and inconclusive evidence, pointing towards methodological limitations associated with using quantity-based physical indicators of human capital to assess cross-country differences. The current study takes cue from this backdrop and proposes a quality-based indicator of human capital that incorporates quality-differences in the education systems. Furthermore, it incorporates inward foreign direct investment as an additional spillover channel and evaluates the findings of CH on domestic productivity. The extent to which knowledge spillovers from international trade and FDI overlap in shaping domestic productivity in the presence of human capital is examined. Finally, the gap towards the technology frontier and its effect on international knowledge spillovers is tested.

Employing cointegration estimation procedure on 20 European countries during 1995–2010, the productivity enhancing effects of FDI-related spillovers as well as import-related spillovers are confirmed. Looking closely at the inter-relationship between knowledge spillovers from trade and inward FDI, our results provide strong support for a complementary relationship between the two. This suggests that not only do these channels directly affect domestic productivity through greater knowledge spillovers, they also complement each other, resulting in a larger overall impact on productivity. The results are robust to model specifications, and to the best of our knowledge, constitute the first novel finding of this study. With respect to human capital, we construct a quality-adjusted indicator by weighing Barro and Lee (2010) quantity-based measure with S&T journal publications and patent applications, and find a direct as well as moderating effect of human capital on domestic productivity. Last but not least, we investigate the catching up hypothesis to test whether technologically lagging countries benefit more from international knowledge spillovers than countries closer to the technological frontier. However, contrary to our a-priori expectation, we do not find support for this argument, for FDI or for import-related spillovers.

While providing important implications relating to the literature on economic growth and human capital, our study is not free from limitations. First, the use of publications and patents as the proxy for quality of education has its limitations. Since publications largely represent only a small proportion of highly qualified academicians, it is difficult to generalize the results to the whole population, especially in the case of developing countries. However, since we do not have so-called developing countries in our sample, this problem might not be significant. Similarly, patents represent a very specific type of innovative activities that can be patented. The standardized tests such as TIMSS can be used as more generalizable quality proxies subject to data availability. Second, our analysis can be greatly improved by the use of bilateral industry level data. In the absence of a rich database at this moment, it is not possible to estimate the knowledge component of FDI using CH methodology. Third, since our sample covers 20 European countries, external validity is limited. Finally, future research can also point towards explaining the phenomenon on micro- and meso-levels of analysis.

**Acknowledgments** Authors gratefully acknowledge the financial support from DFG RTG 1411 "The Economics of Innovative Change". Authors are also thankful to the comments and suggestions from the participants of 15th International Joseph A. Schumpeter Society Conference in Jena and 7th Jena Summer Academy. Thanks is also due to Dr. Charles McCann for proofreading. The usual disclaimers apply.

# Appendix

**Table 4** Advantages and disadvantages of different proxies for quality of human capital

| Proxies | Advantages | Disadvantages/limitations |
|---|---|---|
| TIMMS, PISA, PIAAC | Comprehensive test that includes many countries<br>Many students examined at a time<br>Homogenous test provides comparable results | Periodic tests, hence not available, for long time periods |
| International mathematical | Available for many countries | Only six students assessed per country |
| Olympiad (IMO) | Available for long time periods<br>Homogenous test provides comparable results | Specific to mathematics |
| Journal publications | Provides good approximation for the final output of the education system<br>Not specific to a particular field of study<br>Available through various sources | Nationality of the authors is not available, therefore it is impossible to connect the publications based on author-origin<br>Only provides output of the researchers |
| Patents | Patents cover a broad range of technologies<br>Available from many different sources, both in aggregated and disaggregated forms<br>Data are available for almost all countries for long period of time | Not all inventions are patented. Some technical fields are more likely to patent than others. Moreover, non-technical fields rarely patent<br>Processes innovations are very important but are rarely patented<br>Patents (as well as publications) may only be indicative of quality of education 20 years ago. |

Patents—OECD Compendium of Patent Statistics 2008

**Table 5** OECD Technology intensity classification

| High-technology industries | Medium-high-technology industries |
|---|---|
| Aircraft and spacecraft | Electrical machinery and apparatus |
| Pharmaceuticals | Motor vehicles, trailers and semi-trailers |
| Office, accounting and computing machinery | Chemicals excluding pharmaceuticals |
| Radio, TV and communications equipment | Railroad equipment and transport equipment |
| Medical, precision and optical instruments | Machinery and equipment |
| Medium-low-technology industries | Low-technology industries |
| Building and repairing of ships and boats | Manufacturing; Recycling |
| Rubber and plastics products | Wood, pulp, paper, paper products, printing and publishing |
| Coke, refined petroleum products and nuclear fuel | Food products, beverages and tobacco |
| Other non-metallic mineral products | Textiles, textile products, leather and footwear |
| Basic metals and fabricated metal products | |

*Source*: http://www.oecd.org/science/inno/48350231.pdf
Only medium-high and high-tech industries used in the analysis for international trade

**Table 6** Correlation table

| | (i) | (ii) | (iii) | (iv) | (v) | (vi) |
|---|---|---|---|---|---|---|
| (i) log(TFP) | 1.000 | | | | | |
| | – | | | | | |
| (ii) log(R&D) | 0.129 | 1.000 | | | | |
| | (0.020) | – | | | | |
| (iii) ImportSpill | −0.264 | −0.323 | 1.000 | | | |
| | (0.000) | (0.000) | – | | | |
| (iv) log(HCQ) | 0.258 | 0.466 | −0.721 | 1.000 | | |
| | (0.000) | (0.000) | (0.000) | – | | |
| (v) log(FDI) | 0.495 | 0.435 | −0.084 | 0.221 | 1.000 | |
| | (0.000) | (0.000) | (0.129) | (0.000) | – | |
| (vi) log(Gap) | 0.034 | −0.255 | 0.341 | −0.584 | −0.232 | 1.000 |
| | (0.544) | (0.000) | (0.000) | (0.000) | (0.000) | – |

*p*-Values in parenthesis

## *A.1 Country-Wise Time Plots of Variables*

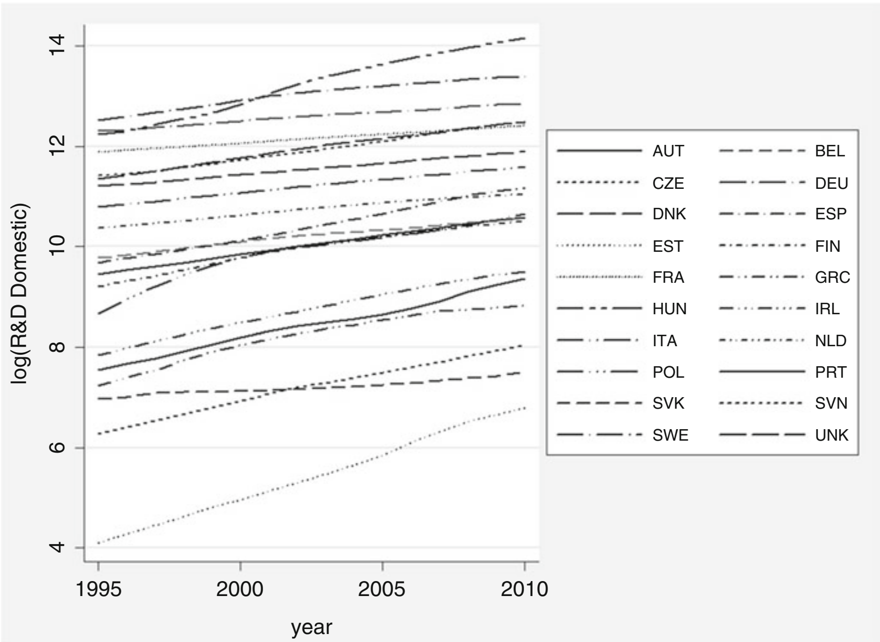


**Fig. 3** log(R&D Domestic)

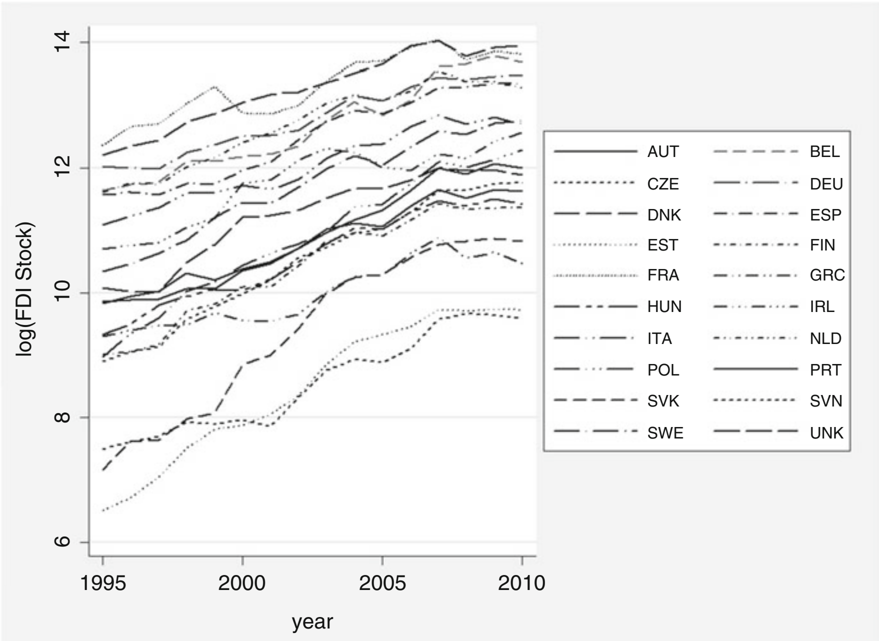


**Fig. 4** log(FDI Stock)

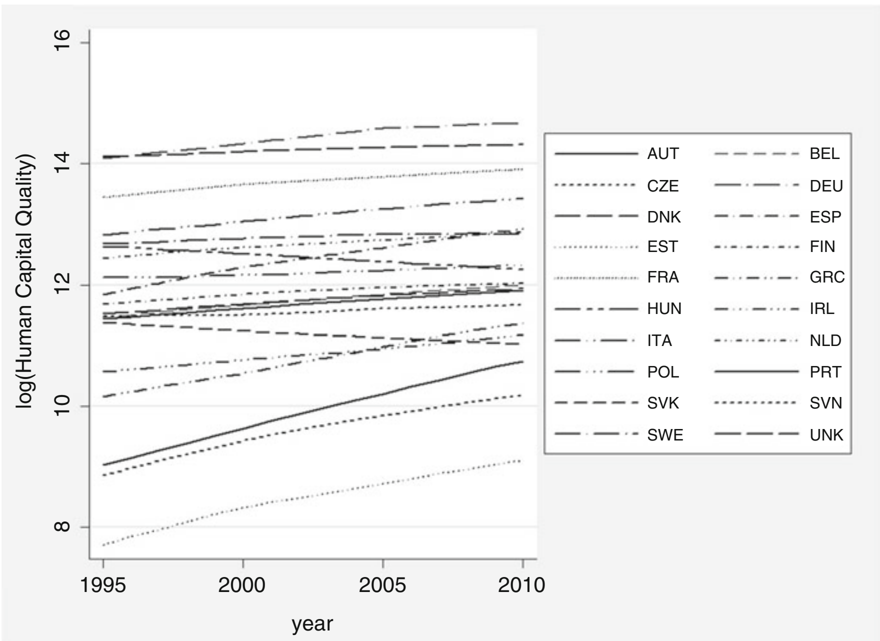


**Fig. 5** log(Human Capital Quality)

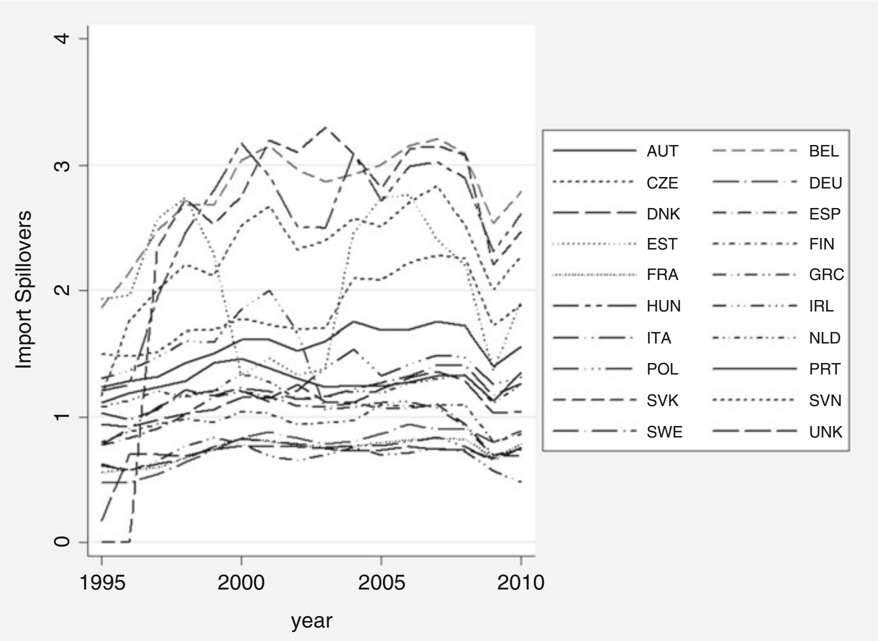


**Fig. 6** Import related spillovers

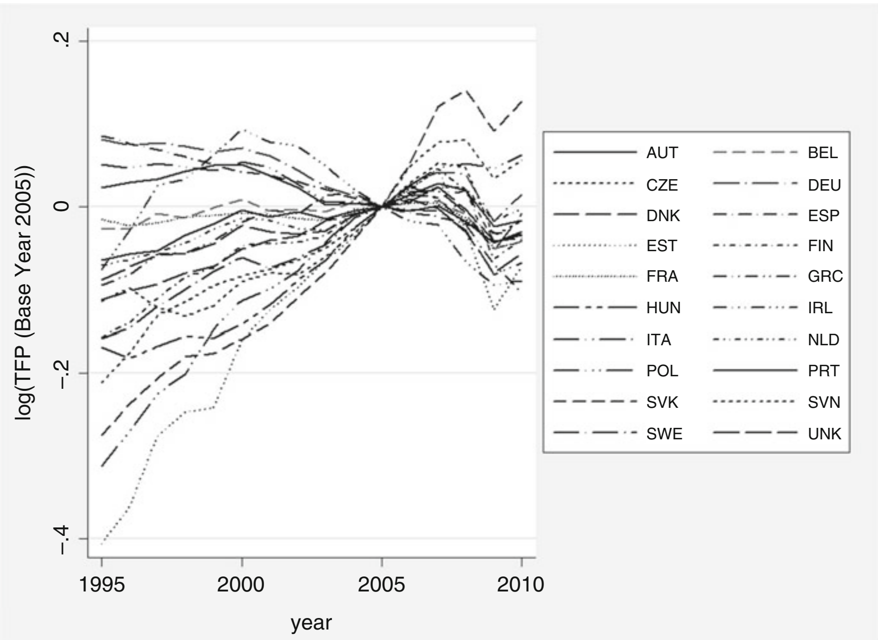


**Fig. 7** log(Total Factor Productivity: Base Year = 2005)

**Table 7** Estimation results: traditional human capital

| | Model(1a) | Model(2a) | Model(3a) |
|---|---|---|---|
| log(R&D) | 0.26*** | 0.30*** | 0.36*** |
| | (0.03) | (0.03) | (0.03) |
| ImportSpill | 1.44*** | −0.35 | −0.45*** |
| | (0.24) | (0.56) | (0.07) |
| log(HC) | 0.86*** | 1.09** | 0.71*** |
| | (0.11) | (0.51) | (0.09) |
| log(FDI) | 0.07*** | 0.16** | 0.39*** |
| | (0.01) | (0.07) | (0.05) |
| log(FDI) × log(HC) | | −0.09 | |
| | | (0.06) | |
| ImportSpill × log(HC) | | 0.38 | |
| | | (0.48) | |
| log(FDI) × ImportSpill | | | 0.65*** |
| | | | (0.07) |
| $R^2$ | 0.964 | 0.979 | 0.976 |
| Adjusted $R^2$ | 0.957 | 0.974 | |
| No. of observations | 300 | 300 | 300 |
| Pedroni | 6 out of 11 | 6 out of 11 | 6 out of 11 |
| Kao cointegration test | −3.21*** | −2.58*** | −2.59*** |

Dependent variable is log(TFP)
Null hypothesis for cointegration test is "no cointegration"
Pedroni test results presented above are number of significant test results out of 11
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

## *A.2 Additional Estimation Results with Traditional Barro-Lee Type Human Capital Variable*

### A.2.1 Brief Overview of Cointegration

Data in macroeconomics generally possess a strong deterministic trend, especially when there is a sufficiently long time series. The variables in such cases are generally non-stationary (that is, they do not have a constant mean and variance over time). In time series, when variables are non-stationary, conventional estimation techniques, such as ordinary least squares, are expected to be driven by spurious correlation (Phillips 1986). Engle and Granger (1987) show that linear combination of two or more $I(1)$ (non-stationary) variables could be $I(0)$ (stationary) in which case the series are said to be cointegrated. In other words, non-stationary variables are said to be cointegrated if the residuals from their relationship are stationary. By using cointegration, one can use full information embodied in the variables and also use the attractive properties of cointegration techniques such as super consistency when $n$ goes to infinity (Stock 1987). Estimates generated by ordinary least squares, however, do not follow an asymptotic Gaussian distribution, therefore standard testing procedures are invalid unless they are significantly modified. Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) are generally considered as an alternative to simple OLS in the presence of cointegration. Since our data contain relatively large macroeconomic time series of 16 years, we test our variables for unit root, the presence of which motivates the test for cointegration.

In time series, the Engle and Granger (1987) cointegration test is used on $I(1)$ variables to test for cointegration. If the residuals from the regression are $I(0)$ then the variables are said to be cointegrated. On a similar principle, Pedroni (1999, 2004) and Kao (1999) propose cointegration tests for panel data. The Pedroni test consists of several tests under different assumptions on constants and trends across cross-sections. Consider the following regression:

$$y_{i,t} = \alpha_i + \delta_i t + \beta_1 x_{1(i,t)} + \beta_2 x_{2(i,t-1)} + \beta_M x_{M(i,t)} + \varepsilon_{i,t} \tag{10}$$

The variables $x$ and y are assumed to be $I(1)$. The individual constant and trends are represented by $\alpha$ and $\delta$, respectively. The null hypothesis of the test is 'no cointegration'. In the case of no cointegration, residuals $c$ are integrated of order 1. If $c$ is $I(0)$ then the variables are said to be cointegrated. Formally, the null hypothesis of no cointegration implies $\rho = 1$ in Eq. (11).

$$\varepsilon_{i,t} = \rho_i \varepsilon_{i,t-1} + u_{i,t} \tag{11}$$

Pedroni proposes two sets of hypotheses for between and within dimension. Under the test for between dimension, the test allows for different cointegrating relationships across cross-sections, while under the test for within dimension the cointegrating relationship is assumed to be homogenous across cross sections. Eleven statistics are calculated for the Pedroni test under the assumptions described above. For the decision rule, however, there is no concrete guideline for how many tests out of eleven should show a cointegrating relationship. In this study, we reject the null of no cointegration if six out of eleven statistics of Pedroni reject the null of cointegration. Kao (1999) uses the similar approach as that of Pedroni but allows for cross section specific constants and homogenous coefficients in the first stage regressions. The null hypothesis, similar to Pedroni test, is no cointegration. For robustness of the results, we have used both Kao and Pedroni tests for cointegration.

**Table 8** Cointegration tests: detailed

| | Model(1) | Model(2) | Model(3) | Model(4) | Model(5a) | Model(5b) | Model(5c) |
|---|---|---|---|---|---|---|---|
| *Within dimension* | | | | | | | |
| Panel v-statistic | −0.36 | −2.4 | −3.69 | −4.47 | −1.28 | −2.04 | −0.61 |
| Panel rho-statistic | 3.78 | 4.77 | 5.67 | 5.98 | 4.5 | 6.5 | 5.07 |
| Panel PP-statistic | 3.715 | −1.57* | −3.33*** | −8.38*** | −0.03 | −2.33*** | −7.41*** |
| Panel ADF-statistic | −2.69** | −4.59*** | −5.69*** | −4.63*** | 3.52*** | −3.33*** | −4.49*** |
| Weighted-panel v-statistic | −1.72 | −4.02 | −3.17 | −5.43 | −2.88 | −5.77 | −5.15 |
| Weighted-panel rho-statistic | 1.74 | 3.81 | 4.86 | 6.01 | 3.48 | 5.43 | 4.98 |
| Weighted-panel PP-statistic | −1.84** | −7.65*** | −7.69*** | −13.2*** | −3.77*** | −14.73*** | −11.89*** |
| Weighted-panel ADF-statistic | −4.62*** | −7.47*** | −7.21*** | −5.92*** | −2.14** | −4.06*** | −4.38*** |
| *Between dimension* | | | | | | | |
| Group rho-statistic | 3.73 | 5.63 | 6.41 | 7.55 | 5.72 | 7.23 | 6.74 |
| Group PP-statistic | −0.17 | −10.82*** | −14.68*** | −20.17*** | −2.88*** | −20.35*** | −17.38*** |
| Group ADF-statistic | −3.33*** | −5.96*** | −7.39*** | −7.12*** | −1.61* | −5.79*** | −5.88*** |
| Kao residual cointegration test | −1.94** | −2.43*** | −3.66*** | −4.24*** | −2.26** | −2.91*** | −2.92*** |

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